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Adaptive Transmission Planning: Implementing a New Paradigm for Managing Economic Risks in Grid Expansion

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We Must Consider Our Uncertain Future

The problem of *whether, where, when* and *what type of* transmission facilities should be built to minimize costs or maximize net economic benefits has always been a challenge in the power industry, ever since Edison considered whether longer DC distribution lines (with their high losses) or new power stations should be built to expand his urban markets. Today's planning decisions are so much more complex, as grids cover the continent and new transmission, generation, and demand-side technologies emerge.

Magnifying the complexity is our highly uncertain future. Actually, uncertainty has never been a really “new” problem to the transmission planners, but they had more urgent problems to address back then. Over the past three decades, planners have been busy planning the expansion of the transmission network so it can effectively play its indispensable role in developing economically efficient and environmentally sustainable markets. Tools have been developed to estimate the benefits of grid enhancements in terms of system reliability, increased energy trade, and decreased pollution emissions. Many of these tools take the form of optimization methods that identify network configurations from the thousands or millions of possibilities that are potentially advantageous and so deserve more detailed analysis. In this article, we argue that these tools need to be enhanced to deal with the newest challenge: that of managing the profound uncertainties that face the industry.

The twists and turns of the power industry over the past decades have taught us that to disregard uncertainty can be costly and even fatal to companies. Does the phrase “stranded assets” sound familiar? How many readers remember WPPSS (aptly pronounced “whoops”, which stands for Washington Public Power Supply System) and their nuclear plans –hopefully you didn’t invest your retirement savings in their bonds? Radical changes in the industry include but are not limited to new environmentally policies, declined and even disappeared load growth, and the expansion of new clean energy technologies. In the 1960’s, a prominent industry forum labelled the ugliness of overhead distribution lines as the greatest

environmental issue, while 7% annual load growth was the norm. Nuclear and oil fired generation grew rapidly, and soon thereafter President Carter was to outlaw use of natural gas in new power plants as too “low” a use for that scarce fuel.

More changes are certain to come, but their nature and magnitude is highly uncertain in this rapidly changing world. The future of carbon policy, the impact of electric vehicles, distributed resources, and smart grid technologies on load growth, the role of storage and central station renewables, and the roller coaster of fuel prices are just some of the risks we face. Depending on what happens in the future, transmission facilities added today may provide far more value than planners anticipate, or may turn out to be costly stranded assets. Transmission planning tools need to recognize these uncertainties. Importantly, they need to properly evaluate the flexibility that investments provide for adapting to the possible future twists and turns. Most of today’s tools consider just one possible future trajectory of loads, policies, and costs when maximizing the economic benefits of investment, and therefore cannot quantify the economic value of this flexibility. As a result, such deterministic (single scenario) tools will undervalue investments that make the system more adaptable, while overvaluing grid investments that are tailored for one future scenario but that may hem in the system and leave it vulnerable to other possible futures.

Three Key Considerations

For the above reasons, the next generation of transmission planning tools needs to recognize three key considerations when quantifying the many types of economic benefits that new transmission investments can provide. These include system-level interactions among transmission and generation investments; variation in generation and load conditions and uncertainty concerning long-run drivers of supply and demand conditions; and the ability to adapt the system as conditions change in unexpected ways.

- To recognize *system-level interactions* is to address two questions: how do transmission reinforcements interact with each other and with generation? In particular: (1) How do proposed transmission facilities interact with each other, resources, and the rest of the network to determine overall system economic and environmental performance? And: (2) How might siting and operating decisions by investors in generation and other resources be affected by the availability of transmission resources? Ideally, grid planning should anticipate how generation investments might shift in response to transmission investment, which would represent a “pro-active” or “anticipative” transmission planning paradigm. This paradigm can be implemented by co-optimizing transmission and generation investment, if it is assumed that generation markets are competitive while grid owners plan the grid and price transmission in order to maximize net benefits of the power system.
- Planning methods should consider *many scenarios of both short-term variations and long-run uncertainties*: In the short-run, how does a proposed

investment enhance a system's ability to take advantage of short-run resource and load diversity? A method must be able to consider many possible operating conditions in order to properly evaluate tradeoffs between focusing investment on the best quality renewable resources versus the benefits of drawing on diverse resources across a large region. In the long-run, how does the investment contribute to the system's robustness in the face of the profound long-run policy, technology, and economic changes that might occur over the assets' 40 or more-year lifetime? Given the uncertainties, what investments can be made now with confidence, and which ones should be deferred until more is known?

- The ability of a system to cope with long-run uncertainties depends in large measure on its *adaptability*. There are several dimensions to adaptability. First, would a particular proposed transmission addition open up alternative operational and planning responses to future developments, or does it foreclose them? Second, is flexibility in timing of investments; it is important to consider how uncertainty could affect the optimal timing of a proposed transmission addition. For instance, in the face of uncertainty, postponing commitments to obtain more information or resolve uncertainties about, e.g., the future of climate policy could be optimal. Is the best response to long-run uncertainties to delay transmission investments in order to avoid the risk of stranded assets by waiting until uncertainties are resolved? A third dimension is portfolio diversification: might the best response to uncertainty be to build a larger portfolio of transmission. Extra lines might then act as "insurance" against the uncertainties, for instance by ensuring access to a wider range of possible developable renewable resources.

In the rest of this article, we describe how today's transmission planning tools are being enhanced to include these three key features. *Co-optimization* models identify economically attractive transmission additions while simultaneously anticipating how the grid investments could affect where and what type of generation investment will take place. *Stochastic* models consider how today's transmission investments would fare under each of multiple possible futures, while *multistage* models also recognize how the grid and generation mix can be modified in the future as the uncertainties unfold. Together, stochastic multi-stage co-optimization models for implementing adaptive grid planning have the potential to identify transmission investments to make today that best position the grid for maximizing future economic and sustainability benefits under the full range of future possibilities.

Existing Optimization Methods for Economic Planning of Transmission

Optimization-based planning tools commonly used for transmission planning studies have a number of widely acknowledged limitations. Two of them are shortcomings relative to the above three key considerations: supply resources and transmission

investments are optimized independently, while the effect of long run technological, economic, and policy uncertainties on transmission economics is either ignored or assessed through sensitivity analyses that cannot identify the mix of transmission investments that optimize probability-weighted costs and benefits. A third potential limitation is that the impact of variable generation on the need for operational flexibility is often greatly simplified. Below, we briefly summarize available software and their limitations; the interested reader is referred to the detailed reviews provided by Lumberras and Ramos and Krishnan et al.

The most common approach that planners use is detailed production cost modeling tools to assess the economic performance of pre-defined transmission and generation configurations. These tools optimize generation dispatch in order to simulate how energy markets utilize transmission, and can successfully capture the rich diversity of constraints and costs in an actual system. Examples of such tools include PSS-E®, GridView®, SDDP®, and PROMOD IV®. However, these commercial modeling packages do not optimize network topology and do not automatically suggest the most economic transmission investments.

In contrast, a few commercial models, like NETPLAN®, have topology optimization capabilities made in a chronological way. But these methods assume a fixed scenario of generation build-out (i.e., they are unable to represent how generator siting and investment mix responds to transmission investment) and, furthermore, they do not consider the uncertainties in market and regulatory conditions that are the drivers for generation investment. A notable exception to this is Western Electricity Coordinating Council's (WECC) Long-term Planning Tool, which provides insights on the interactions of generation and transmission investments that could be made ten to twenty years in the future. It does this by iterating between new generation capacity evaluation (using a levelized cost methodology) and transmission investment optimization. Other exceptions include Energy Exemplar's PLEXOS® and PSR's OPTGEN G&T®, which perform simultaneous generation and transmission co-optimization but does not consider long-run uncertainties except through sensitivity analyses.

Thus, current transmission planning methods are limited in their ability to represent uncertainty. Under scenario planning, a range of scenarios are defined, each of which represent one possible combination of future drivers of generation investment, such as load growth, fuel prices, or environmental policies. For each of these scenarios a separate transmission plan is developed using either deterministic optimization (as in NETPLAN) or, more often, by testing various pre-defined plans using production costing models. In some studies, investments that are selected in all or most of the scenario plans are identified as "robust" decisions. Examples of this type of planning approach include the "Multi-Value Projects" identified by the Mid-Continent ISO, and the "least-regret investments" by the California ISO. The central assumption of these heuristic approaches is that investments selected in all or most scenarios provide a hedge against uncertainty and are therefore attractive for development.

However, it has been proven mathematically that optimal stochastic investment strategies (i.e., ones that minimize probability-weighted costs across scenarios, considering adaptability) cannot be constructed through such heuristics. Indeed, a robustness heuristic, like the examples provided above, can perform considerably worse than a deterministic plan if the plans have few overlapping lines, resulting in underinvestment in transmission. Plans that are optimal under uncertainty may not be best for any individual deterministic scenario. For example, a particular transmission investment might perform well in many scenarios because it gives the system some flexibility, for instance, to develop any of several renewable energy zones. But that investment might never be the very best choice in any single scenario of renewable development. However, when considered stochastically, that line would provide a hedge against uncertainty and could be optimal overall. For this reason, scenario planning and heuristics are unable to quantify the full value of alternatives that increase the adaptability of transmission plans. We give an example later in this paper of two such lines that our stochastic planning methodology identified.

Turning to the last potential limitation, short-run variability and the ability of transmission, generation, and demand-side investments to provide the operating flexibility to manage it are key considerations. The rapid development of renewables, driven for example by California's 50% by 2030 goal, will be a major driver of inter-regional transmission investments. Transmission expansion can be justified both by the need to access high quality resources as well as the need to take advantage of resource diversity. But many evaluations of transmission expansion consider only a small set of years or hours, such as the California ISO Transmission Economic Assessment Methodology or ICF's Integrated Planning Model (IPM©), or do not incorporate ramping and unit commitment constraints which can greatly impact the ability of generation, storage, and demand resources to respond to renewable variability.

So there is a need for co-optimizing investments in transmission and generation while considering long-run uncertainties, as well as for addressing renewable variability in long-term expansion planning applications. There is a particular need for developing and applying methods for realistically large networks, such as the Western Interconnection, and representing the needed uncertainties to address the problem in a meaningful way.

The Philosophy of Stochastic Programming

We now describe a stochastic optimization model for transmission planning that attempts to address that need. Stochastic optimization is an approach that allows a decision maker to ask:

What network investments should be made now, and what investments should be deferred and made later, considering multiple possibilities of what might happen and how those investments affect the ability of a system to adapt to later changes?

Figure 1 contrasts the basic difference between the deterministic and stochastic planning philosophies, in which the former chooses today's and tomorrow's investments considering a single scenario of future conditions (top of figure), while the latter considers multiple scenarios simultaneously (bottom). In that figure, the logic of the decision process is shown as a decision tree, in which time proceeds from left to right. Three steps of the decision process are shown, consisting of two decision stages separated by uncertain scenarios, although optimization models can include more than three such steps. The steps are:

1. "Here and now" decisions—i.e., commitments that are made before it is known how longer-run uncertainties will be resolved—are shown as the first square node on the left. In our application, these are transmission and generation investments made in years 1-10 (2015-2024). A particular decision (one set of transmission investments, for instance) can be represented as a single arc leaving that node to the right. Multiple alternatives are in general shown as multiple arcs. The dashed line shows which alternative is chosen by the optimization, while the double slash indicates an inferior alternative. Figure 1 shows just two alternatives per decision node, but in the actual application there are a large number of possible combinations of transmission and generation investments that are implicitly defined by the decision variables and constraints in the stochastic optimization.
2. Then proceeding to the right, the decision maker will next encounter chance nodes (round nodes). These represent the range of possible scenarios (one per arc leaving the node to the right) of what could happen to long-run demand growth, prices, policies, etc. Each of the scenarios has a probability. In Figure 1, the scenarios shown are five scenarios (or "study cases") considered by WECC in their 2013 Transmission Expansion Planning Policy Committee (TEPPC) process.
3. Finally, for each scenario, there is a decision node (square node) to its right representing a set of later "wait and see" or "recourse" decisions that are made after it is known which scenario has occurred. In our application, these are investments in years 11-20 (2025-2034). What choice (dashed line) is made in this second stage is conditioned on the scenario and the first-stage decision; as a result, the decisions made if, say, wind development costs fall dramatically can differ if instead a scenario occurs in which wind costs are unchanged as time progresses. Thus, recourse decisions allow the system to adapt to technology, economic, and policy changes embodied in the scenarios.

In the stochastic decision structure in the lower part of Figure 1, an optimal solution, or "decision strategy" is a single set of choices in the first decision stage plus a set of choices for each of the scenarios that are considered in the second decision stage (dashed arrows in figure 1 lower part). Thus, stage one decisions are commitments

that must be lived with in all scenarios, but stage two decisions are tailored to the scenario. In other words, one strategy for all scenarios.

In contrast, a conventional deterministic decision structure is found in the upper half of Figure 1. For *one* scenario (with a probability of 1), the model solves for an optimal transmission expansion strategy (dashed arrows). Sensitivity analyses proceed by substituting another scenario, resulting in a different optimum. In other words, one strategy for one scenario.

Figure 1 also illustrates the likelihood that the first stage plan given by stochastic planning (Plan B) could be different from the plan by deterministic planning (Plan A). Under the base case scenario, A has about a \$1 billion lower cost than B, the latter building more backbone reinforcements. The total cost shown (about two-thirds of a trillion dollars) is the present worth of forty years of building and operating the western North American (WECC) grid and power plants. A and B differ in what first stage (years 1-10) transmission lines are built, amounting to \$3.6-\$4.6 billion of investment in our model. However, considering all five of the scenarios from WECC's 2013 TEPPC process, and assuming equal (0.2) probabilities for each, shows that B is instead less expensive by about \$5 billion in expected present worth. Thus, making a naïve decision (A) based on a single scenario instead of the stochastic decision (B) that considers system adaptability under several scenarios could result in a cost penalty of the same order of magnitude as the investments themselves.

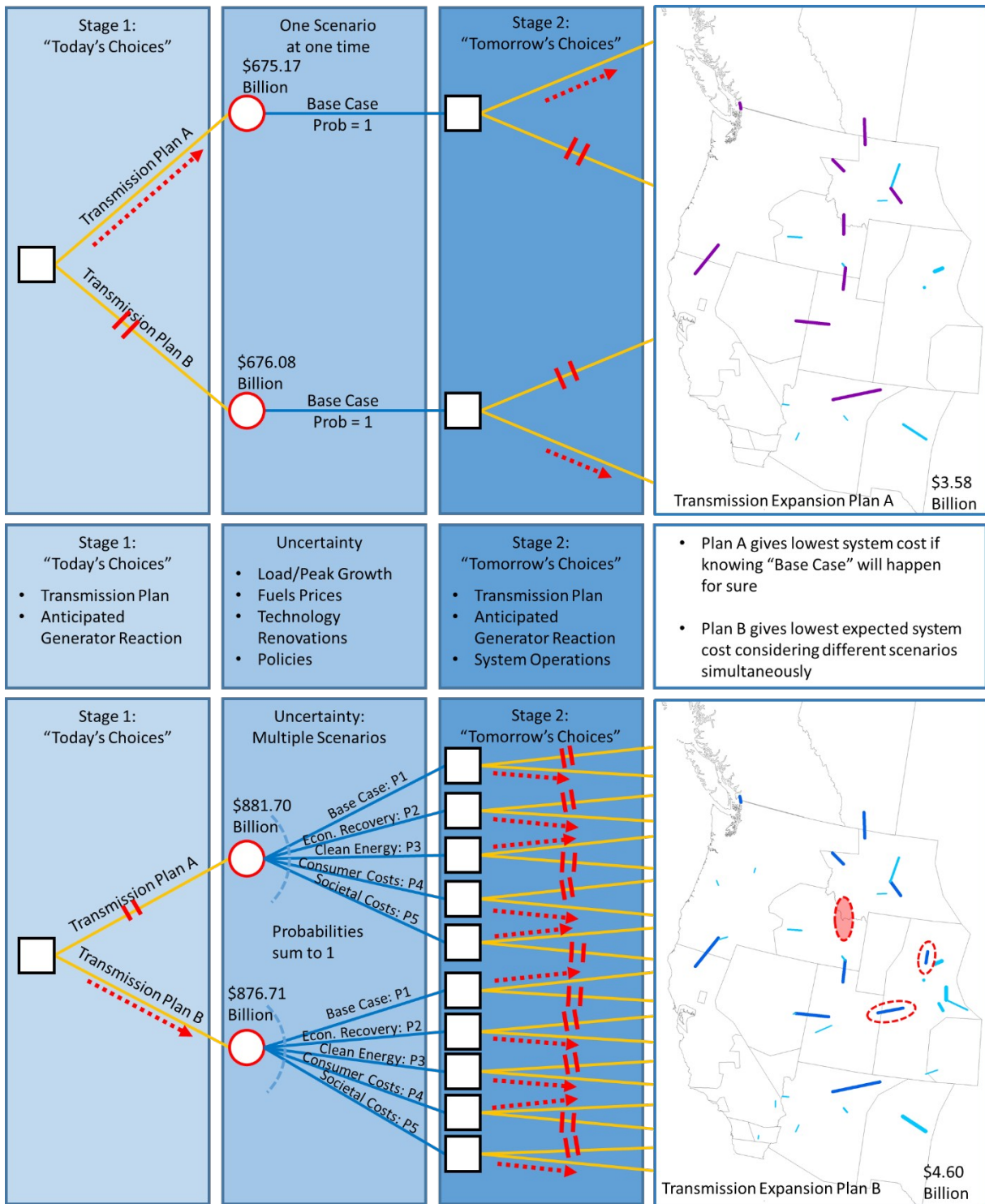


figure 1. Comparison between deterministic planning (top) and stochastic planning (bottom) (illustrated with data from our WECC study). Right: resulting first stage (year 1-10) solutions (dark lines are new backbone lines, light lines are renewable interconnections)

JHSMINE – A Stochastic Transmission Planning Tool

We now describe in more detail an illustrative stochastic analysis using the Johns Hopkins Stochastic Multi-stage Integrated Network Expansion model (JHSMINE), testing its performance with the data from Western Electricity Coordination Council. Figure 2 shows a schematic of the basic steps involved in using JHSMINE, which we describe in this section.

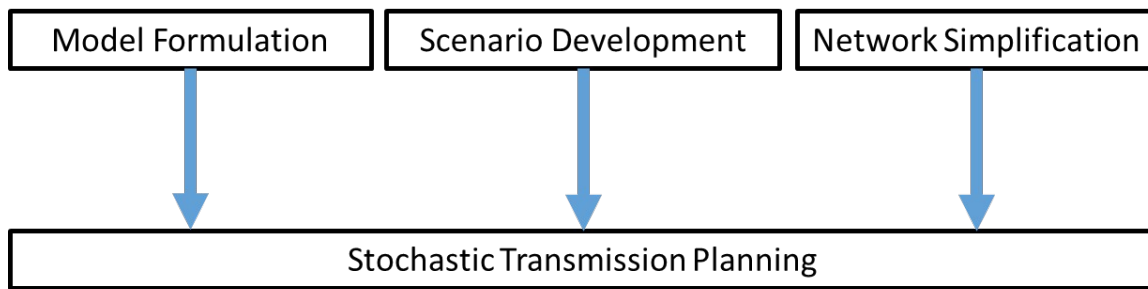


figure 2. Planning schematic of JHSMINE

In the first step, we formulated the model to fully address the key considerations of system-level interactions, future uncertainties, and system adaptability by appropriate definitions of the objective and constraints:

MIN Probability-weighted present worth of transmission & generation capital + operating costs

subject to the following constraints:

- *Short-run operational constraints* (energy balances, Kirchhoff's voltage law to represent parallel flows, capacity limits on plant generation and transmission flow, wind- and solar-output limitations by hour, operating reserve requirements, renewable portfolio standards)
- *Long-run expansion constraints* (siting limitations on the location and capacity of new lines and generation)

This model is structured as a multistage mixed integer linear program which is solved as a single large optimization problem. The stages are the years considered (e.g., years 1-10 investments represent stage 1, years 11-20 investments are stage 2), as shown in Figure 1. Operating hours within each stage are chosen from a representative single year, and are either chronological for representative days (as in our relaxed unit commitment implementation of JHSMINE) or are randomly selected (as in our load duration curve implementation). The resulting model has on the order of 1-3 million variables, depending on the particular formulation, number of scenarios, and number of operating hours.

In the second step, we need a comprehensive set of scenarios (called “study cases” by WECC). The variables that vary among the scenarios should be important: that

is, they would affect the relative desirability of different investments, and there is a reasonably large range of possible values in the future. The only thing we can be sure of is that future behavior of these variables will be different from the past, so their possible ranges, distributions, and correlations must by necessity rely on expert judgment. In the WECC study, JHU collaborated with a group of experts and stakeholders called the Technical Advisory Group (TAG), and developed 20 scenarios to be analyzed. Figure 3 outlines the procedure used to develop the scenarios, with a generic procedure shown on the right and our specific implementation on the left.

In Figure 3, we can see that there are a number of types of judgments that were needed, some of which were made by the TAG experts and some by JHU staff. The members of the TAG picked which variables that they thought would most impact the WECC system, and then provided ranges (i.e., 90% confidence intervals) for each variable. The variables suggested for the WECC study included, among others, natural gas and coal prices, carbon tax, energy growth, peak load growth, renewable portfolio standards, and capital costs of wind, solar, and geothermal plants (table 1). Then the TAG experts considered the five original 2013 TEPPC scenarios and added nine more scenarios (particular combinations of the variables) that they thought were plausible. Based on the information from TAG experts, JHU come up with six more “plug hole” scenarios to cover the full range of uncertain variables. This set of 20 scenarios allowed us to compare the impact of considering no uncertainty (base case only), a restricted set of scenarios (base case plus the other 2013 study cases), and the full set of scenarios upon the results (Figure 4), which we discuss later in this article. In an actual stakeholder-based planning process, the final scenario set would be reviewed and approved by the stakeholder group; however, for the purposes of our methodology demonstration, this was not necessary.

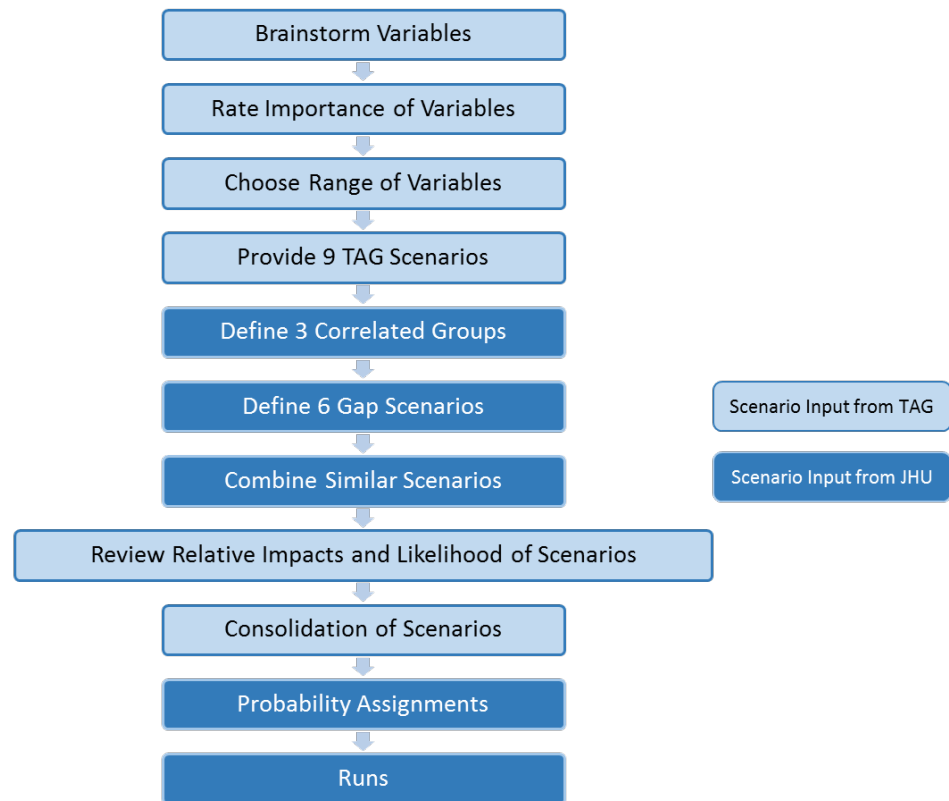


figure 3. Scenario Development procedures in JHU-WECC study

table 1. Variables and their ranges

Variables		Low	High
Fuel & Carbon Prices	Natural Gas (\$/MMBtu)	3.86	14.5
	Carbon (\$/ton)	25.9	87.5
	Coal (\$/MMBtu)	2.24	3.50
Net Energy for Load	Total WECC Load Growth (%/yr)	1.0	1.9
	Energy reductions (%/yr)	0.3	4.0
	Electrification (%/yr)	0.3	1.8
Coincident Peak Demand	System peak growth rate (%/yr)	1.3	1.9
	Policy-driven peak reductions (%/yr)	0.1	3.3
	Policy-driven peak electrification (%/yr)	0.2	0.8
Capital Cost	Onshore Wind(\$/kW)	1569	2065
	Geothermal(\$/kW)	5015	6490
	Solar PV(\$/kW):	2320	4233
	Solar Thermal(\$/kW):	3560	4519

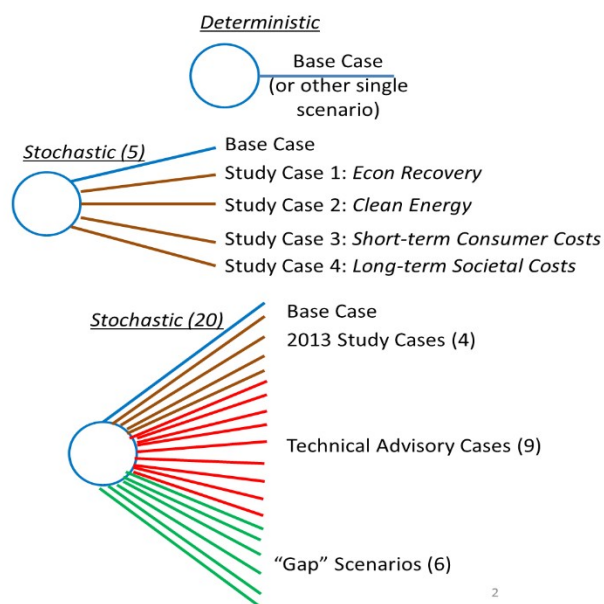


figure 4 Schematic of the change node of stochastic planning under one, five or twenty scenarios

To conclude the scenario creation step of the process, we assigned a probability to each of the 20 scenarios. This probability is used in the objective function to weight the costs occurring in each of the future scenarios. One set of probabilities was based on a “moment matching” procedure that chose scenario probabilities so that the mean and standard deviation of the uncertain variables were consistent with the ranges that the TAG members originally assigned. As a sensitivity analysis we also considered equal probabilities for the scenarios.

With the help of Figure 5, we can discuss in more detail the interactions between the components of JHSMINE (left side of figure) and the uncertainties embodied in the scenarios (right side). For instance, uncertainties regarding whether states will adopt more ambitious Renewable Portfolio Standards (RPS) will affect the model’s constraints upon generation mix, with different renewable targets in different scenarios. As another example, uncertain carbon tax/permit price levels will result in variation among the scenarios in the objective function’s net fuel costs. A third example arises from the lengthy permit licensing times for transmission lines, which results in the possibility of a “failure to launch” for some proposed individual lines. This type of uncertainty is represented by distinct scenarios, some of which omit some planned lines from the model’s grid representation.

The diagram shows many such linkages between the various long run uncertainties and the optimization’s model objective, decision variables, and constraints. However, it is not an exhaustive list of possible sources of uncertainty, and additional ones could be inserted in the blocks on the right. This figure also omits short run variations and risks, such as load/wind/solar variations or N-1 security constraints.

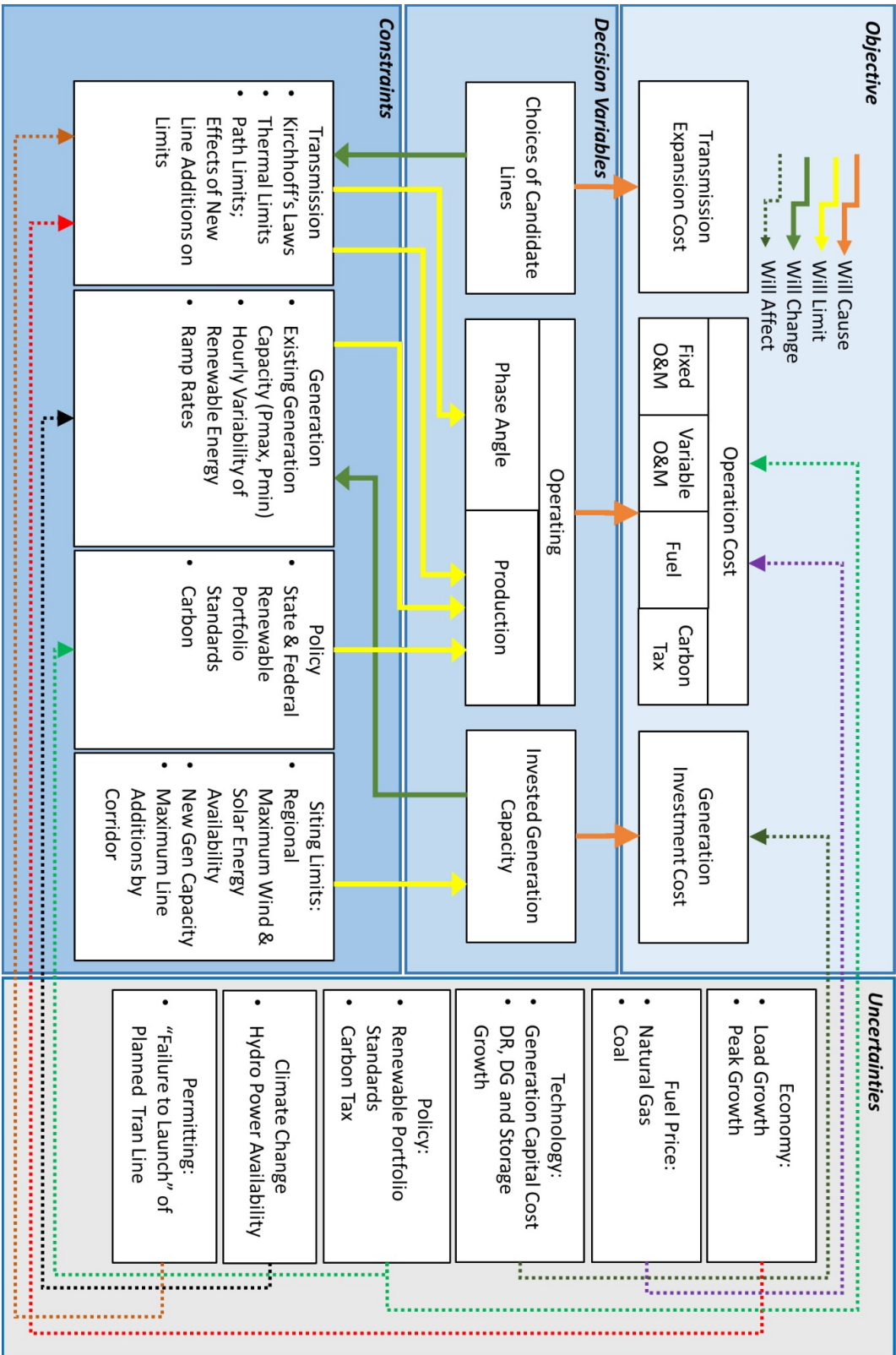


figure 5. Interactions between uncertainties and optimization model components

A simplified network based on the real transmission network is necessary for JHSMINE to run on a university workstation. Thus, in the third major step of the analysis, with the help of colleagues Yujia Zhu and Dan Tylavsky at Arizona State University, we simplified the western interconnection system to a 300 bus DC load flow approximation that preserved the major interregional paths (Figure 6). Such a simplification makes it practical to optimize placement of transmission and generation investments over multiple years, considering numerous wind/solar/load conditions within each year.

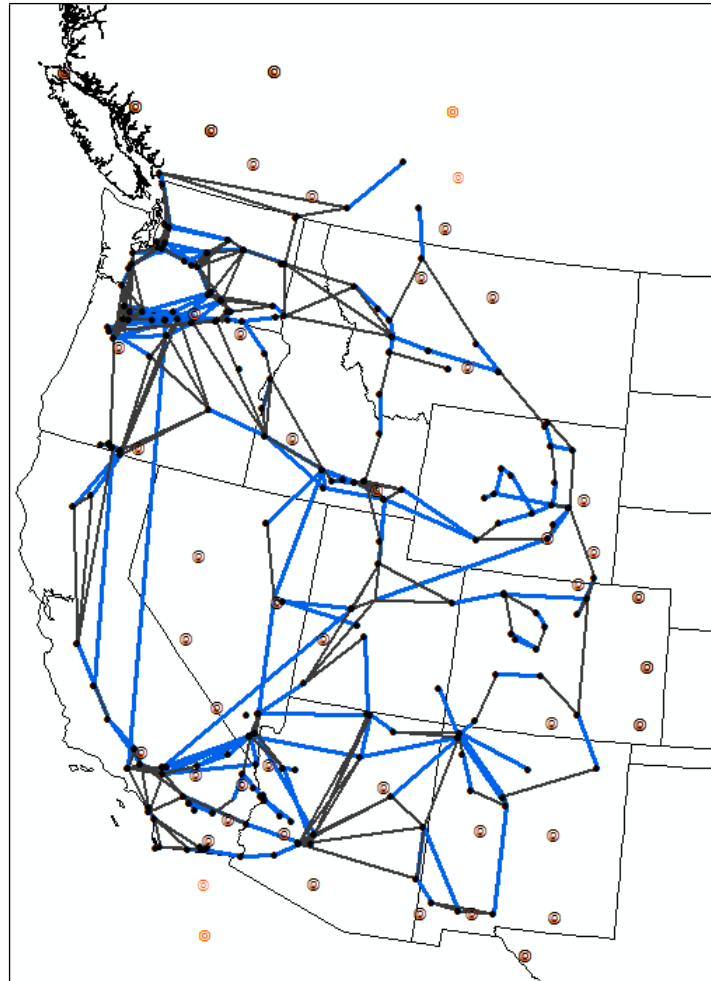


figure 4. 300-bus network used in WECC-JHU study (blue lines are candidate lines that could be chosen by the model, circles are possible renewable hubs)

It Is Possible and Better to Consider All Scenarios in One Run

We now highlight some results of the JHSMINE application to WECC that illustrate the value and insights that can be gained from applying stochastic programming to transmission planning.

First, stochastic programming is feasible. The results from the JHU-WECC studies show that it is practical to identify economically optimal grid additions considering multiple scenarios simultaneously using stochastic programming. The model was able to recommend a set of initial (years 1-10) transmission investments considering multiple scenarios, together with later (years 11-20) investments that adapted to the particular scenario that was realized, while anticipating how generator investment would react to those grid enhancements. The model was solved on a lab-level desktop, and the most sophisticated case (300 bus network, 20 long run scenarios, 4 million constraints, 3 million continuous variables, and 1113 binary variables for transmission investments) took 4 hours to run. This means a more detailed network with more scenarios can be solved on an enterprise-level server/cluster.

In other words, to derive an adaptive transmission plan for an uncertain future is very practical. What makes such a model particularly useful is that, once set up, a single analyst can alter assumptions and develop a new optimal transmission-generation investment scenario quickly. In contrast, traditional planning processes, which develop generation investment build-out scenarios and then evaluate a number of alternative transmission configurations with production models, can take person-weeks of effort per scenario. Stochastic optimization can therefore allow analysts to consider the impact of many more sets of assumptions upon transmission recommendations.

Second, near-term investments recommended by stochastic programming are more cost-effective. Depending on the assumptions and the version of JHSMINE that is used, our stochastic solutions based upon 5 or 20 scenarios (bottom, Figure 4) perform \$1B to \$12B better (probability-weighted present worth) than the investments recommended by a deterministic model based upon WECC's 2013 base case scenario (top, Figure 4). For instance, as mentioned above, the base case solution, which yields the first stage investments on the upper right of Figure 1, results in expected costs (over the five WECC TEPPC study cases) that are \$5 billion higher than a stochastic solution considering all five of those scenarios (lower right, Figure 1).

Third, stochastic plans are more robust against scenarios not considered than deterministic plans. The advantage of the stochastic solution grows to \$11 billion if the base case and 5 scenario stochastic solutions are compared considering all twenty scenarios. It turns out that in this case, considering just 5 scenarios versus using all 20 in the stochastic optimization yielded the same backbone grid investments—so considering even a few scenarios may capture most

of the economic benefit of stochastic planning. The 5 scenario solution did appreciably better than the base case solution in a large majority of the other 15 scenarios. Therefore, by choosing investments that give the system flexibility to adapt to the considered 5 scenarios, the system also turns out to adapt more readily to the other 15 scenarios that weren't considered. So it appears that the transmission investments recommended by stochastic programming are inherently robust against future uncertainties compared to deterministic solutions, even if they were not explicitly modeled.

Fourth, stochastic planning outperforms the heuristics based on identifying lines common to several deterministic plans. As noted earlier, the California ISO and Mid-Continent ISO have promoted heuristic planning processes that identify “robust” solutions as ones that include lines that appear in several or all deterministic solutions. This planning approach is represented by heuristic versions of JHSMINE models. The best performing heuristic we tested is to build lines now that are built in years 1-10 in a majority of the 20 individual deterministic models (one model for each of the 20 scenarios). It does better than the base case-only solution, but over \$1 billion worse than the stochastic solutions that considered either 5 or 20 solutions. Other heuristic solutions based on choosing lines that appear in all the deterministic solutions, or that are chosen by any of the solutions, do much worse. Thus, although such a heuristic sometimes (but not always) does better than planning for a single scenario, the stochastic solution does even better.

Potential Improvements

The successful use of multiple scenarios to represent of social, economic, environmental uncertainties in an economic optimization model for transmission, together with the expected cost savings resulting from adaptive planning, demonstrate that it can be both feasible and cost-effective to consider uncertainty in a stochastic planning tool. However, under present computing technology, there are limits to the complexity that can be represented—consideration of more than 300 aggregated buses, 20 representative hours per year, and 20 scenarios strained the capabilities of our workstations. As computational capabilities improve, the models can be made more realistic by considering more buses, hours, and scenarios, and by improving the realism of the models. Here are some ways in which the realism of the models can be improved.

- *An enlarged pool of candidate lines.* In a linearized DC model, each line in each year and scenario is represented by a binary variable, and the number of binaries that can be considered in our mixed integer linear programming-based formulation is relatively limited.
- *Generation unit commitment constraints.* With the higher penetration of variable renewables, flexibility of fossil generation becomes a greater concern, and it becomes more important to represent start-up costs, minimum output constraints, and other details of unit commitment.

- *More decision stages.* Figure 1 shows a two stage problem in which all uncertainties are eliminated by the second stage. However, in reality, uncertainties remain in the future, while there are also intermediate decision stages that give the system more flexibility, such as obtaining permits for a corridor prior committing to construction.
- *DC load flow with losses, AC load flow models, and FACTS devices,* which would more accurately represent the costs of transmission as well as options to manage those costs.

Inclusion of some or all of these features would enable stochastic planning models to provide even more useful insights to the planning process.

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For Further Reading:

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